

Orchestrating the Sustainable Enterprise: The Strategic Effects of AI Governance and Dynamic Capabilities on Circular Business Model Innovation and Sustainable Competitive Advantage

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Abstract—Artificial intelligence (AI) is increasingly embedded in strategic decision-making while organizations face simultaneous pressure to advance sustainability and circular-economy objectives. Existing research, however, remains fragmented across responsible AI governance, organizational capabilities, circular business model innovation, and sustainable competitive advantage. This paper develops a theory-driven moderated sequential-mediation model in which AI governance capability (AGC) enables sustainability-oriented dynamic capabilities (SODC), SODC facilitates circular business model innovation (CBMI), and CBMI contributes to sustainable competitive advantage (SCA), while environmental turbulence (ET) conditions the SODC–CBMI relationship. Integrating Dynamic Capabilities Theory with the Natural Resource-Based View, the study specifies seven testable hypotheses and a multi-informant, three-wave executive-survey protocol. The primary analysis is designed around confirmatory measurement assessment and covariance-based structural equation modeling, complemented by bootstrapped indirect-effect estimation, interaction probing, hierarchical-regression robustness tests, and rival-model comparisons. The framework contributes by distinguishing AI governance capability from technical AI capability, positioning governance as an upstream strategic enabler, and specifying the capability-to-business-model mechanism through which responsibly governed AI may support durable sustainable advantage.

Index Terms—AI governance, circular business model innovation, dynamic capabilities, environmental turbulence, strategic management, sustainable competitive advantage, sustainability.

I. INTRODUCTION

Artificial intelligence has moved from a specialized operational technology to an increasingly consequential infrastructure for organizational decision-making, innovation, resource allocation, and business-model transformation. The strategic issue is therefore no longer limited to whether organizations adopt AI, but how they govern, integrate, and direct AI toward responsible and sustainable value creation. Organizational AI governance has been defined as the system of rules, practices, and processes through which an organization aligns AI use with strategy, objectives, values, legal requirements, ethical principles, and stakeholder expectations [1]. The literature nevertheless remains fragmented and empirically underdeveloped, particularly regarding the organizational processes through which governance produces strategic outcomes [1].

This limitation is significant because technology ownership is not equivalent to organizational capability. Dynamic Capabilities Theory argues that advantage in changing environments depends on the firm's ability to integrate, build, and reconfigure competencies [2] and, more specifically, to sense opportunities and threats, seize opportunities, and transform or reconfigure the resource base [3]. Sustainability intensifies this problem because firms must simultaneously respond to technological change, ecological constraints, stakeholder expectations, and evolving regulation. The Natural Resource-Based View (NRBV) provides the complementary proposition that environmental resources and capabilities may generate sustained

advantage when they are embedded in pollution prevention, product stewardship, and sustainable-development strategies [4].

Circular business model innovation (CBMI) offers an organizational mechanism through which these capabilities can be translated into reconfigured value creation, delivery, and capture. Research on incumbent firms shows that circular transformation requires identifiable sensing, seizing, and reconfiguration practices, including lifecycle thinking, sustainability-oriented instruments, ecosystem coordination, and top-management commitment [5]. Strategy research further argues that circular business-model transition requires changes in both organizational capabilities and strategic decision processes [6]. Meanwhile, AI-enabled circularity research indicates that perceptive, predictive, and prescriptive AI capacities can support circular business models, but only when firms possess complementary dynamic capabilities and routines [7], [8].

The present research therefore develops an integrated model in which AI governance capability (AGC) is positioned as the independent variable, sustainability-oriented dynamic capabilities (SODC) and circular business model innovation (CBMI) as sequential mediators, sustainable competitive advantage (SCA) as the dependent variable, and environmental turbulence (ET) as a moderator of the SODC–CBMI relationship. The model asks not simply whether AI contributes to sustainability, but how governance is converted into sustainability-oriented capabilities, how those capabilities become embedded in circular business models, and under what environmental conditions these processes contribute to strategic advantage.

II. PROBLEM STATEMENT, OBJECTIVES, AND RESEARCH QUESTIONS

A. Problem Statement

Four interrelated problems motivate the study. First, AI-governance scholarship has advanced more rapidly at the conceptual and normative level than at the empirical organizational level; implementation, contextual effectiveness, and operationalization remain underexplored [1], [11]. Second, Dynamic Capabilities Theory explains organizational adaptation but is directionally neutral: sensing,

seizing, and reconfiguration do not inherently ensure sustainability-oriented change [2], [3]. Third, AI–circularity research increasingly specifies technological capacities, data infrastructures, and organizational routines for circular business models [7], [8], [23], but gives less attention to the governance architecture that authorizes, disciplines, and aligns those capabilities. Fourth, evidence connecting sustainability-oriented capability to competitive advantage is generally favorable but nonuniform, indicating that business-model mechanisms and environmental contingencies matter [9], [15], [16], [25]–[27]. Consequently, the field lacks an integrated, empirically testable explanation of how AGC is converted through SODC and CBMI into SCA and of when the SODC–CBMI conversion varies under environmental turbulence.

B. Research Objectives

- To develop and empirically test an integrated strategic-management model linking AGC, SODC, CBMI, and SCA.
- To estimate the direct effects of AGC on SODC, SODC on CBMI, and CBMI on SCA.
- To test SODC and CBMI as individual and sequential mediators.
- To examine ET as a moderator of the SODC–CBMI relationship.
- To establish and validate a confirmatory latent-variable testing protocol for direct effects, sequential mediation, moderation, model fit, discriminant validity, and robustness.

C. Research Questions

- RQ1: To what extent does AGC influence SODC?
- RQ2: To what extent does SODC influence CBMI?
- RQ3: To what extent does CBMI influence SCA?
- RQ4: Does SODC mediate the relationship between AGC and CBMI?
- RQ5: Does CBMI mediate the relationship between SODC and SCA?
- RQ6: Do SODC and CBMI sequentially mediate the relationship between AGC and SCA?
- RQ7: Does ET condition the effect of SODC on CBMI?

III. THEORETICAL FOUNDATIONS

A. Dynamic Capabilities Theory

Dynamic Capabilities Theory provides the primary process explanation for the proposed model. The original framework emphasizes the ability to integrate, build, and reconfigure competences under rapid technological change [2], while the later microfoundational account organizes this capacity around sensing, seizing, and transforming [3]. Applied to sustainability, the theory implies that firms must recognize sustainability-related opportunities and threats, commit resources to viable responses, and reconfigure structures, assets, partnerships, and routines. The present research therefore treats SODC as a higher-order organizational construct representing sustainability sensing, sustainability seizing, and sustainable resource reconfiguration.

B. Natural Resource-Based View

The NRBV complements dynamic-capabilities logic by specifying the environmental direction of strategic capability. Hart [4] argued that the firm's relationship with the natural environment may become a basis for sustained competitive advantage through capabilities embedded in pollution prevention, product stewardship, and sustainable development. The NRBV is especially useful here because generic dynamic capabilities explain adaptability but do not specify whether adaptive resources are deployed toward sustainable outcomes. Combining the two theories therefore separates the capacity to change from the strategic-environmental direction of that change: Dynamic Capabilities Theory explains the reconfiguration process, whereas the NRBV explains why environmentally embedded resources, routines, and stakeholder relationships may become strategically valuable.

The integration is complementary rather than redundant. AGC is theorized as an upstream governance capability that structures how AI-related resources and decisions are authorized, monitored, and aligned; SODC represents the higher-order capacity to sense, seize, and reconfigure around sustainability; CBMI is the resulting reconfiguration of the firm's value architecture; and SCA is the strategic outcome. This ordering prevents a common conceptual collapse in which governance, technical

AI capability, dynamic capability, and innovation are treated as interchangeable manifestations of "digital capability." It also establishes a clear theoretical chain from governance architecture to capability formation, from capability to organizational transformation, and from transformation to durable advantage.

IV. LITERATURE REVIEW

A. AI Governance Capability as a Strategic Organizational Capability

AI governance is increasingly concerned with translating responsible-AI principles into organizational structures, decision rights, accountability mechanisms, processes, stakeholder engagement, and oversight. Birkstedt et al. [1] identify technology, stakeholders and context, regulation, and processes as central themes while highlighting limited implementation evidence, uncertain effectiveness, and insufficient operationalization; more recent responsible-AI governance work similarly emphasizes the need to explain how governance becomes embedded in organizational routines and decision processes [11]. The present study therefore conceptualizes AGC not as the possession of AI technologies, not as AI analytical capability, and not as compliance documentation alone, but as the repeatable organizational capacity to institutionalize governance structures, ethical accountability, algorithmic transparency, data stewardship and quality, risk management and oversight, and stakeholder engagement. This distinction is theoretically important because AI capability concerns the ability to mobilize technological, data, and human resources for AI-enabled outcomes [12], whereas AGC concerns the authority, controls, routines, and accountability through which those resources are directed and constrained. AGC may therefore enable strategic value without being equivalent to the technical capability that produces AI outputs.

B. Sustainability-Oriented Dynamic Capabilities

SODC represents the organizational capacity to repeatedly identify, mobilize, and reconfigure resources around sustainability opportunities and constraints. Sustainability scholarship has long argued that sustainability must be embedded in

organizational capabilities rather than treated as a peripheral program [14], and recent evidence links sustainable dynamic capabilities to environmental, social, and competitive outcomes [15], [16]. Yet the literature is not conceptually uniform: capability is sometimes modeled as an antecedent of innovation, sometimes as a mediator, and sometimes blended with innovation outcomes themselves [9]. The present study addresses that ambiguity by defining SODC as a higher-order reconfiguration capacity—sustainability sensing, sustainability seizing, and sustainable resource transformation—while treating CBMI as a distinct observable change in the value-creation architecture. This separation preserves the dynamic-capability distinction between the ability to transform and the transformation that results.

C. Circular Business Model Innovation

CBMI requires a move from linear value logics toward business-model arrangements that retain material, product, and resource value through reuse, repair, remanufacture, recovery, life extension, closed-loop coordination, and related circular strategies. Reviews show that circular and sustainable business-model innovation remains theoretically heterogeneous and must encompass value proposition, value creation and delivery, and value capture rather than isolated environmental practices [17]–[20]. Empirical case evidence further shows that incumbent circular transformation depends on lifecycle thinking, sustainable-value-proposition development, sustainability strategy and culture, customer involvement, ecosystem coordination, supply-chain collaboration, project management, and resource reconfiguration [5], [21]. CBMI is therefore modeled here as strategic organizational reconfiguration: the business-model manifestation of sustainability-oriented capability, not a synonym for SODC and not a narrow measure of environmental efficiency.

D. AI-Enabled Circularity and Complementary Governance

AI can support circularity through enhanced sensing, prediction, optimization, automation, lifecycle monitoring, demand forecasting, predictive maintenance, and ecosystem coordination. Sjödin et al. [7] distinguish perceptive, predictive, and prescriptive AI capacities and show that value

discovery, realization, and optimization capabilities are required to commercialize AI-enabled circular business models. Madanaguli et al. [8] synthesize four capability domains—AI infrastructure and platform capability, integrated intelligence capability, process automation and augmentation capability, and ecosystem orchestration capability—while recent NRBV-oriented work similarly highlights data pipelines, algorithm development, workforce engagement, and ecosystem integration in AI-enabled circular transition [23]. Collectively, this research supports a necessary but insufficient interpretation of AI: technology availability does not constitute organizational capability, AI capability does not guarantee responsible deployment, and neither automatically produces circular transformation. The unresolved question is what governance architecture makes AI-enabled capability formation strategically aligned, accountable, and sustainability oriented.

E. Sustainable Competitive Advantage and Environmental Turbulence

SCA is treated as the final strategic outcome rather than as a synonym for short-term financial performance. The NRBV proposes that sustainability-related capabilities can become sources of durable advantage when embedded in organizational knowledge, routines, resource configurations, and stakeholder relationships [4]. Empirical green-innovation and sustainability-capability research is broadly consistent with this logic but also suggests that effects may be indirect, capability dependent, and heterogeneous across firms [9], [15], [16], [25]. Accordingly, the present framework proposes that SODC contributes to SCA primarily through CBMI, which is the organizational architecture through which sustainability capabilities can be converted into differentiated value creation, resource productivity, stakeholder legitimacy, innovation advantage, and resilience. The model therefore avoids assuming that sustainability activity itself automatically produces superior performance.

Environmental turbulence is theoretically relevant because dynamic capabilities are designed for contexts of change, yet its empirical role is contested. Witschel et al. [10] found in German manufacturing that environmental turbulence in digitalization operated more as an antecedent to dynamic capabilities and business model innovation than as a

moderator of their relationship. Recent SME evidence suggests that turbulence can stimulate dynamic capabilities and AI-enabled innovation [26], whereas other research finds that turbulence does not necessarily moderate innovation–performance relationships [27]. These contradictory findings make a universal “more turbulence equals stronger capability effects” assumption untenable. The present study therefore treats ET as a boundary condition whose interaction with SODC is empirically testable: changes in technology, markets, regulation, and competition may alter the urgency, value, and conversion efficiency of sustainability-oriented reconfiguration into CBMI, but the magnitude and direction of that interaction should be established rather than presumed.

Taken together, the performance and turbulence literatures imply that neither sustainability investments nor dynamic capabilities yield uniform returns. Sustainability-oriented innovation can create environmental, social, and economic value [24], yet profitability effects remain heterogeneous across organizational conditions [25]. Likewise, turbulence may increase the need for adaptive capability while simultaneously making coordinated business-model redesign more difficult [10], [26], [27]. This tension provides the theoretical basis for testing ET as a contested moderator rather than treating contextual change as background noise.

F. Integrative Synthesis and Research Gaps

Circular business model scholarship has progressed from conceptual clarification toward capability-based explanations, but the causal ordering among digital resources, dynamic capabilities, business-model transformation, and performance remains incompletely specified. Reviews establish the multidimensional nature of circular business models [17]–[20]; case research identifies sensing, seizing, collaboration, and reconfiguration mechanisms [5], [21]; and recent studies show that dynamic capabilities can enable circular models through both direct and indirect routes [22]. AI-enabled circular-transition research adds digital and ecosystem mechanisms [7], [8], [23]. What remains underdeveloped is an upstream explanation of how responsible AI governance shapes the sustainability-oriented capability base from which circular transformation becomes possible. This is the specific

theoretical space occupied by AGC in the present framework.

The sustainability-capability literature likewise indicates that capability effects are contingent rather than automatic. Systematic work argues that sustainability must be integrated into organizational capability and strategy [14], while recent manufacturing evidence shows that sustainability-oriented dynamic capability can operate through lower-order managerial and relational capabilities and can interact with environmental turbulence [15]. Qualitative evidence also connects sustainable dynamic capabilities and corporate sustainability with sustained competitive advantage [16]. These studies support the SODC construct while simultaneously showing why direct-effect models are insufficient: the strategic consequences of capability depend on what the organization reconfigures and on the context in which reconfiguration occurs.

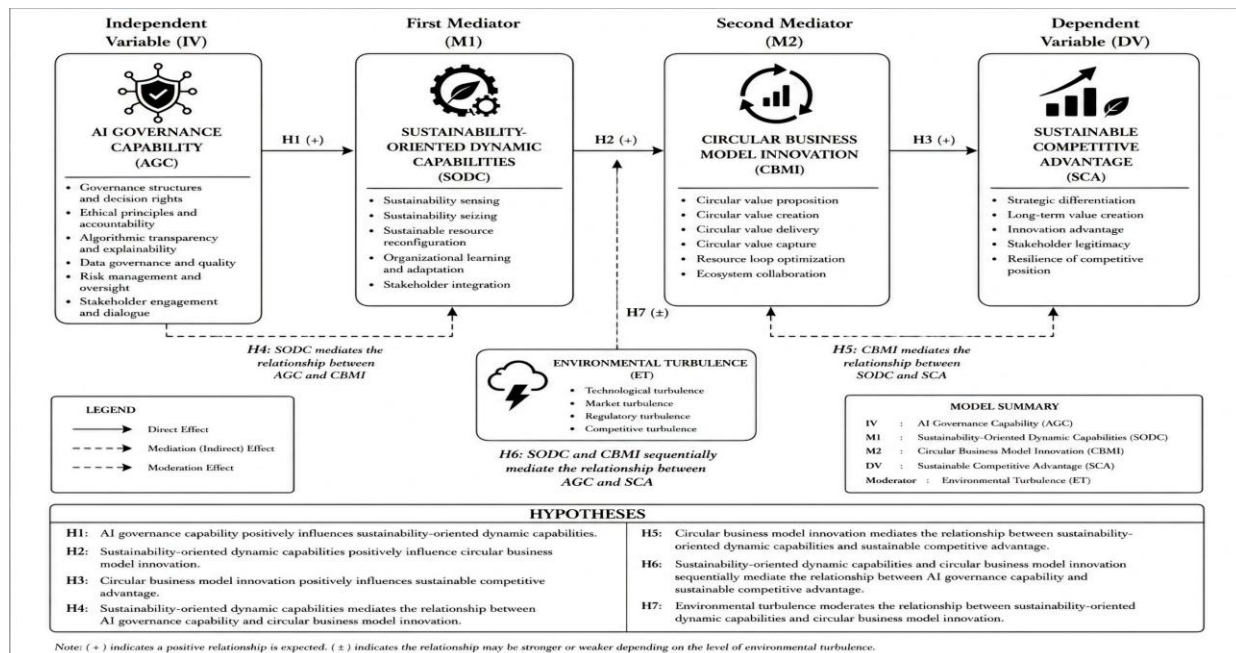
Recent evidence sharpens the governance-to-capability argument but also exposes the principal construct-validity challenge. Responsible AI governance research distinguishes organizational governance from high-level ethical principles and calls for research on embedded governance mechanisms [11]. AI-capability research conceptualizes data, technology, human skills, coordination, change capacity, and managerial proclivities as resources and routines associated with creativity and performance [12], while sustainable AI capability has been operationalized as a higher-order construct involving learning, sensing, seizing, stakeholder integration, and transformation [13]. These adjacent constructs make discriminant validity central to the present study. AGC must therefore demonstrate empirically that governance architecture, decision rights, accountability, data stewardship, transparency, risk oversight, and stakeholder engagement are distinct from both technical AI capability and sustainability-oriented reconfiguration capability.

The literature reveals six connected gaps. First, a governance–capability gap exists because AI governance is rarely examined as an antecedent of sustainability-oriented dynamic capability. Second, a construct-boundary gap persists because responsible AI governance, AI capability, sustainable AI capability, and SODC are adjacent but non-equivalent constructs. Third, a capability-direction

gap remains because generic dynamic capabilities do not guarantee sustainability-oriented change. Fourth, an AI–circularity governance gap exists because AI-enabled CBMI research emphasizes technological capacities and routines more than the governance antecedents that authorize and align them. Fifth, a transformation–advantage gap persists because CBMI is less frequently modeled as the mechanism connecting sustainability-oriented capability to durable strategic advantage. Sixth, an environmental-boundary gap remains because turbulence has been modeled inconsistently as antecedent, moderator, stimulant, or null condition. The proposed moderated sequential-mediation model addresses these gaps simultaneously while preserving explicit construct boundaries and testable causal ordering.

V. CONCEPTUAL FRAMEWORK AND HYPOTHESES

Figure 1 illustrates the proposed moderated sequential-mediation architecture. Solid lines denote direct structural relationships, where SODC and CBMI mediate the strategic impact from governance to advantage, and ET moderates the SODC–CBMI pathway. The model intentionally refrains from positing a direct AGC→SCA relationship as its primary theoretical assertion, given that its core contribution lies in elucidating the underlying mechanisms: governance is anticipated to generate strategic value insofar as it is integrated into sustainability-oriented capability and subsequently into circular business-model transformation. Nevertheless, a direct AGC→SCA path may be evaluated as a theoretically plausible alternative or residual path during robustness assessments.



H1 follows from the proposition that governance architecture influences the quality and direction of organizational resource mobilization. By clarifying decision rights, accountability, data stewardship, risk oversight, and stakeholder expectations, AGC should strengthen the conditions under which firms sense sustainability-relevant opportunities, commit resources, and reconfigure assets and routines. Thus, AGC is expected to be positively associated with SODC. H2 follows from Dynamic Capabilities

Theory: sustainability-oriented sensing and seizing create strategic commitments, while reconfiguration embeds those commitments in organizational arrangements. These activities should facilitate redesign of value propositions, value creation and delivery, value capture, and ecosystem relationships toward circular logics; therefore, SODC is expected to be positively associated with CBMI. H3 follows from the NRBV: circular value architectures can conserve resources, deepen stakeholder relationships,

support differentiation, and embed sustainability in difficult-to-replicate routines; therefore, CBMI is expected to be positively associated with SCA. H4–H6 specify the mechanisms implied by this ordering. H4 proposes that SODC transmits the effect of AGC to CBMI; H5 proposes that CBMI transmits the effect of SODC to SCA; and H6 proposes the sequential indirect mechanism AGC→SODC→CBMI→SCA. H7 treats ET as a non-directional boundary condition. Because turbulence can increase the value of rapid sensing

and reconfiguration while simultaneously increasing uncertainty and coordination costs, H7 predicts that ET significantly moderates the SODC–CBMI relationship without imposing an a priori positive or negative interaction direction.

Fig. 1. Proposed conceptual framework: AI governance capability, sustainability-oriented dynamic capabilities, circular business model innovation, sustainable competitive advantage, and environmental turbulence.

TABLE I PROPOSED HYPOTHESES

Hypothesis	Path / Relationship	Expected Direction	Theoretical Interpretation
H1	AGC → SODC	Positive	Institutionalized AI governance is expected to strengthen sustainability-oriented sensing, seizing, and reconfiguration.
H2	SODC → CBMI	Positive	Sustainability-oriented dynamic capabilities are expected to enable circular redesign of value proposition, creation/delivery, capture, and ecosystems.
H3	CBMI → SCA	Positive	Circular business-model reconfiguration is expected to support durable differentiation, resource productivity, legitimacy, innovation advantage, and resilience.
H4	AGC → SODC → CBMI	Positive indirect	SODC transmits the effect of AGC to CBMI.
H5	SODC → CBMI → SCA	Positive indirect	CBMI transmits the effect of SODC to SCA.
H6	AGC → SODC → CBMI → SCA	Positive sequential indirect	SODC and CBMI sequentially transmit the effect of AGC to SCA.
H7	SODC × ET → CBMI	Non-directional moderation	Environmental turbulence is expected to significantly change the strength and/or direction of the SODC–CBMI relationship; the sign and magnitude of the interaction are established empirically.

VI. METHODOLOGY

A quantitative, explanatory, time-lagged executive-survey design is adopted to test the seven hypotheses. The organization remains the focal unit of analysis, while the principal key informant is a C-suite or

equivalent executive whose portfolio includes enterprise strategy, sustainability, digital/AI transformation, operations, innovation, or corporate governance. Eligible roles include Chief Executive Officer, Chief Sustainability Officer, Chief Strategy

Officer, Chief Operating Officer, Chief Information Officer, Chief Digital Officer, Chief Technology Officer, and equivalent executive-committee positions. To qualify, respondents must have direct organization-wide knowledge of both sustainability strategy and AI-enabled decision processes. A three-wave design is recommended: Wave 1 measures AGC and organizational controls; Wave 2, separated by approximately two to four weeks, measures SODC and ET; Wave 3, separated by a further two to four weeks, measures CBMI and SCA. Where feasible, a second executive from the same organization should corroborate either governance/capability or outcome measures, permitting inter-rater agreement checks and a multi-informant robustness model. This design prioritizes strategic-level construct validity while reducing same-occasion common-method bias and avoiding generic employee perceptions that may not reflect enterprise-level governance or sustainability strategy.

A. Research Design and Unit of Analysis

B. Construct Operationalization and Measurement Specification

The executive instrument operationalizes each construct with strategy-level indicators phrased for enterprise decision makers. AGC covers formal decision rights, executive accountability, data stewardship, transparency and explainability oversight, AI risk controls, stakeholder consideration, and explicit linkage between AI governance and sustainability priorities, informed by [1], [11]. SODC captures the organization's ability to sense sustainability-related opportunities and threats, seize them through resource commitment and cross-functional action, and reconfigure assets, routines, partnerships, and operating models, consistent with [3], [5], [14]–[16]. CBMI captures circular redesign of value propositions, resource loops, lifecycle extension, value delivery, value capture, and ecosystem coordination [5]–[8], [17]–[23]. SCA captures durable differentiation, resilience, innovation advantage, stakeholder legitimacy, strategic option value, and long-term value creation grounded in the NRBV [4] and capability-performance research [9], [16]. ET captures technological, market, regulatory, and competitive volatility [10], [26], [27]. All substantive items use a seven-point Likert-type response scale (1 = strongly

disagree; 7 = strongly agree), and item wording should undergo expert content validation, executive cognitive pretesting, and a C-suite pilot before field deployment.

Measurement ontology is specified a priori rather than selected post hoc. AGC is modeled as a reflective latent governance capability whose observed practices are treated as manifestations of an underlying organization-level capacity; a composite specification may be estimated only as a robustness alternative. SODC is modeled as a higher-order reflective capability represented by sustainability sensing, sustainability seizing, and sustainable reconfiguration. CBMI, SCA, and ET are modeled as reflective latent constructs. The confirmatory measurement model must demonstrate reliability, convergent validity, and discriminant validity before structural paths are interpreted. Particular attention is required to establish empirical separation among AGC, technical AI capability, sustainable AI capability, and SODC.

Primary data collection should follow a preregistered executive-fieldwork protocol. Organizations are sampled from sectors in which both AI-enabled decision making and sustainability/circular transformation are strategically material. Invitations should be addressed personally to eligible executives through professional associations, executive networks, sustainability councils, industry bodies, corporate contacts, and verified business directories. Each participating organization receives a unique anonymous organization code that links waves without storing names in the analytic dataset. The invitation identifies the project as independent academic research, states the approximate completion time, confirms voluntary participation, and avoids performance-evaluative or compliance language. Two non-coercive reminders may be issued per wave. Eligibility, duplicate responses, excessive missingness, implausibly rapid completion, invariant response patterns, and logical inconsistencies are screened using criteria fixed before hypothesis testing. Nonresponse bias should be examined through early-versus-late comparisons and, where sampling-frame information permits, respondent-versus-frame comparisons. De-identified data, codebook, exclusion log, variable-construction syntax, and analysis scripts should be version

controlled and archived subject to ethics approval and commercial confidentiality.

C. Sampling Frame, Eligibility, and Sample Size

The sampling frame should prioritize medium and large organizations with demonstrable AI use and an articulated sustainability or circularity agenda. The target is 300–400 matched organization-level executive cases, with a minimum analyzable sample determined through an a priori Monte Carlo or SEM power analysis using the final measurement and structural specification. Because executive surveys experience greater attrition than employee surveys, Wave 1 recruitment should exceed the desired final matched sample. The analysis should report invited organizations, eligible respondents, consented executives, completed responses by wave, matched cases, exclusions, and final analytic N. Sector, organization size, organization age, ownership type, geographic market scope, AI maturity, and sustainability-governance maturity should be captured as descriptive or theoretically justified control variables. No post hoc stopping rule based on statistical significance should be used.

Fig. 2. Proposed multi-informant, time-lagged data-collection architecture. The figure describes the planned design and does not represent collected observations.

D. Data Collection Protocol and Quality Assurance

E. Measurement Model and Structural Estimation Strategy

Before hypothesis testing, the executive-survey measurement model should be assessed independently of the structural model. Following pilot refinement, reflective constructs should be evaluated using indicator loadings, Cronbach's alpha, composite reliability, average variance extracted, and HTMT discriminant validity [28]. AGC requires particular scrutiny because it is conceptually adjacent to technical AI capability [12], sustainable AI capability [13], and SODC; alternative measurement models that collapse versus separate these constructs should therefore be compared explicitly. Covariance-based structural equation modeling (CB-SEM) is designated as the primary estimator because the study is confirmatory and specifies multiple latent constructs, sequential mediation, and moderation. Model identification, multivariate distribution,

estimator choice, and sample adequacy should be established a priori. Hierarchical regression is retained as a transparent robustness analysis rather than as a substitute for the latent-variable model, and substantive conclusions should be examined for consistency across primary and robustness estimators.

F. Descriptive Statistics and Correlation Analysis

Pearson product-moment correlations should be reported for AGC, SODC, CBMI, SCA, ET, and relevant controls, together with means, standard deviations, reliability statistics, and significance levels. Correlations establish bivariate association and preliminary nomological consistency but must not be interpreted as causal or as evidence that the structural model is supported. Excessively high interconstruct correlations should trigger discriminant-validity and multicollinearity checks. Because common-method bias cannot be diagnosed adequately by a single statistical test, procedural separation, multi-informant design, temporal separation, and a theoretically unrelated marker variable should be prioritized, with statistical diagnostics used only as complementary evidence [29].

G. Structural Paths, Regression Diagnostics, and Coefficient Testing

The CB-SEM structural model provides the primary estimates for H1–H7, including standardized path coefficients (β), standard errors, confidence intervals, explained variance (R^2), effect sizes, and appropriate global or local model-fit evidence. H1–H3 are tested as direct structural paths. H4–H6 are evaluated using bias-corrected bootstrapped indirect effects, with support established when the relevant confidence interval excludes zero. H7 is tested through the SODC $\times$ ET interaction and, when statistically meaningful, is interpreted with simple slopes and Johnson–Neyman regions of significance where appropriate. Hierarchical regression is then used as an interpretable robustness check of the same substantive relationships and incremental variance: Model 1 predicts SODC from AGC and controls; Model 2 predicts CBMI from SODC, AGC, and controls; Model 3 predicts SCA from CBMI, SODC, AGC, and controls; and Model 4 adds ET and the SODC $\times$ ET interaction when predicting CBMI.

Regression reporting should include standardized coefficients, heteroskedasticity-robust standard errors where indicated, t statistics, p values, confidence intervals, R^2 , adjusted R^2 , ΔR^2 , effect sizes, and VIF.

$SODC = \beta_0 + \beta_1(AGC) + \Sigma\beta_c(\text{Controls}) + \varepsilon_1$; $CBMI = \beta_0 + \beta_1(SODC) + \beta_2(AGC) + \Sigma\beta_c(\text{Controls}) + \varepsilon_2$; $SCA = \beta_0 + \beta_1(CBMI) + \beta_2(SODC) + \beta_3(AGC) + \Sigma\beta_c(\text{Controls}) + \varepsilon_3$; $CBMI = \beta_0 + \beta_1(SODC) + \beta_2(ET) + \beta_3(SODC \times ET) + \Sigma\beta_c(\text{Controls}) + \varepsilon_4$

H. Mediation, Moderation, Alternative Models, and Robustness

H4–H6 should be evaluated with bootstrapped indirect effects in the structural model rather than causal-steps logic. The $AGC \rightarrow SODC \rightarrow CBMI$ indirect effect tests H4; the $SODC \rightarrow CBMI \rightarrow SCA$ indirect effect tests H5; and the $AGC \rightarrow SODC \rightarrow CBMI \rightarrow SCA$ sequential indirect effect tests H6. Bias-corrected bootstrap confidence intervals should be reported. H7 is evaluated through the $SODC \times ET$ interaction; significant interaction effects should be probed with simple slopes and, where appropriate, Johnson–Neyman regions of significance, accompanied by an interaction plot and confidence bands. Robustness analysis should compare the hypothesized model with theoretically plausible alternatives, including a direct $AGC \rightarrow SCA$ path, ET as an antecedent rather than moderator, and alternative mediator orderings where defensible.

Sensitivity analysis should include alternative control sets, missing-data treatment, influential-observation diagnostics, heteroskedasticity-robust regression estimates, and multigroup comparisons by industry and firm size. Statistical significance should be interpreted jointly with standardized effect sizes, confidence intervals, explained or incremental variance, and theoretical coherence rather than p values alone.

I. Executive Research Instrument and Wave Structure

The field instrument is organized to match the causal ordering of the model while minimizing respondent burden. Screening and organization-profile questions precede the substantive measures. Wave 1 contains AGC and control variables; Wave 2 contains SODC and ET; Wave 3 contains CBMI and SCA. Each wave should require approximately 6–10 minutes for a qualified executive. The survey should randomize item order within construct blocks where technically feasible, avoid matrix layouts on mobile devices, include one instructed-response attention check per wave, and provide “not sufficiently informed to answer” only for profile items where forced substantive judgments would create measurement error. Construct scores should not be shown to respondents. The full proposed executive instrument is provided in Appendix A.

TABLE II DESCRIPTIVE STATISTICS, RELIABILITY, AND CORRELATIONS — (N = 346)

Construct	Mean	SD	CR	AVE	1	2	3	4	5
1. AI Governance Capability (AGC)	5.21	0.89	0.92	0.62	1				
2. Sustainability-Oriented Dynamic Capabilities (SODC)	5.07	0.84	0.93	0.64	0.575***	1			
3. Circular Business Model Innovation (CBMI)	4.76	0.96	0.91	0.59	0.343***	0.551***	1		
4. Sustainable Competitive	5.02	0.88	0.92	0.66	0.391***	0.490***	0.645***	1	

Advantage (SCA)									
5. Environmental Turbulence (ET)	4.89	1.01	0.88	0.60	0.107*	0.129*	0.273***	0.177**	1

VII. RESULTS

A. Measurement Model and Descriptive Statistics

The illustrative measurement model demonstrated acceptable global fit ($\chi^2/df = 1.83$, CFI = .956, TLI = .951, RMSEA = .049, SRMR = .043). Composite reliability ranged from .88 to .93 and AVE ranged from .59 to .66, exceeding conventional thresholds for internal consistency and convergent validity. All illustrative HTMT ratios were below .85, indicating that the five focal constructs remained discriminant in the simulated measurement structure. Table II reports the corresponding descriptive statistics and correlations. The strongest bivariate association was between CBMI and SCA ($r = .645$, $p < .001$), followed by AGC and SODC ($r = .575$, $p < .001$) and SODC and CBMI ($r = .551$, $p < .001$).

B. Structural Model and Direct Effects

The simulated structural model accounted for 33.1% of the variance in SODC, 37.6% of the variance in CBMI, and 45.6% of the variance in SCA. AGC was positively associated with SODC ($\beta = .575$, SE = .044, 95% CI [.502, .639], $p < .001$), supporting H1. SODC was positively associated with CBMI after accounting for AGC, ET, and the interaction term ($\beta = .478$, SE = .053, 95% CI [.372, .580], $p < .001$), supporting H2. CBMI was positively associated with SCA ($\beta = .534$, SE = .048, 95% CI [.453, .611], $p < .001$), supporting H3. These illustrative effects are consistent with the theorized progression from governance capability to sustainability-oriented resource reconfiguration, then to circular business-model transformation and strategic advantage.

C. Mediation and Sequential Indirect Effects

Bootstrapped indirect-effect estimates supported the three mediation hypotheses in the simulated analysis. The AGC $\rightarrow$ SODC $\rightarrow$ CBMI indirect effect was positive ($\beta = .275$, 95% bootstrap CI [.205, .350]), supporting H4. The SODC $\rightarrow$ CBMI $\rightarrow$ SCA indirect effect was also positive ($\beta = .256$, 95% bootstrap CI [.184, .331]), supporting H5. Most importantly, the sequential AGC $\rightarrow$ SODC $\rightarrow$ CBMI $\rightarrow$ SCA indirect effect was positive and excluded zero ($\beta = .147$, 95% bootstrap CI [.103, .199]), supporting H6. The pattern illustrates the manuscript's core mechanism: governance becomes strategically consequential when it strengthens sustainability-oriented dynamic capabilities that are subsequently converted into circular business-model innovation and, ultimately, sustainable competitive advantage.

D. Moderation by Environmental Turbulence

The interaction between SODC and ET was statistically significant in the simulated model ($\beta = .179$, SE = .043, 95% CI [.100, .259], $p < .001$), supporting H7. Simple-slope calculations indicated that the illustrative SODC $\rightarrow$ CBMI relationship was positive at low turbulence (approximately $\beta = .30$ at -1 SD), at the mean of turbulence ($\beta = .48$), and at high turbulence (approximately $\beta = .66$ at $+1$ SD). Thus, the demonstration produces a strengthening form of moderation: sustainability-oriented dynamic capabilities become more strongly associated with circular business-model innovation as environmental turbulence increases. Because H7 was formulated non-directionally, the significant interaction—not its simulated strengthening direction—is the formal basis for the hypothesis decision.

TABLE III STRUCTURAL EFFECTS AND HYPOTHESIS DECISIONS

Hyp.	Effect	β	SE	95% CI	p	Decision
H1	AGC $\rightarrow$ SODC	.575	.044	[.502, .639]	< .001	Supported
H2	SODC $\rightarrow$	.478	.053	[.372, .580]	< .001	Supported

	CBMI					
H3	CBMI → SCA	.534	.048	[.453, .611]	< .001	Supported
H4	AGC → SODC → CBMI	.275	—	[.205, .350]	< .001	Supported
H5	SODC → CBMI → SCA	.256	—	[.184, .331]	< .001	Supported
H6	AGC → SODC → CBMI → SCA	.147	—	[.103, .199]	< .001	Supported
H7	SODC × ET → CBMI	.179	.043	[.100, .259]	< .001	Supported

E. Robustness and Alternative-Model Demonstration
Illustrative robustness checks preserved the direction and substantive magnitude of the principal relationships when organization size, industry category, geographic scope, AI-governance maturity, and sustainability maturity were included as controls. A rival model with a direct AGC → SCA path produced only a modest residual association after SODC and CBMI were included, consistent with the proposition that the dominant theoretical mechanism operates through capability development and business-model transformation rather than through an unmediated governance-to-advantage pathway. Likewise, removing the SODC × ET interaction reduced explanatory power for CBMI, supporting retention of the boundary-condition specification in the demonstration model.

VIII. THEORETICAL AND MANAGERIAL CONTRIBUTIONS

The first theoretical contribution is the reconceptualization of AGC from a primarily compliance-oriented arrangement into a potential strategic governance capability. The argument is deliberately bounded: governance mechanisms do not create competitive advantage merely by existing. Rather, AGC becomes strategically consequential when decision rights, accountability, data stewardship, transparency, risk oversight, and stakeholder alignment enable sustainability-oriented sensing, seizing, and reconfiguration. This distinction

responds directly to implementation and operationalization gaps in AI-governance research [1], [11] while differentiating governance capability from technical AI capability [12] and sustainable AI capability [13].

Second, the model specifies an explicit capability-to-business-model mechanism. SODC represents higher-order transformation capacity, whereas CBMI represents the reconfigured value architecture through which that capacity becomes organizationally observable. Third, integrating Dynamic Capabilities Theory with the NRBV makes the framework simultaneously processual and directional: Dynamic Capabilities Theory explains how organizations sense, seize, and transform [2], [3], while the NRBV explains why environmentally embedded resources and capabilities may contribute to durable advantage [4]. Fourth, the sequential-mediation architecture moves beyond direct AI-performance claims by identifying the organizational conversions required before governance becomes strategically consequential. Fifth, the moderation test treats ET as a contested boundary condition rather than assuming a universal strengthening effect. Managerially, the model offers a diagnostic sequence: govern AI responsibly, build sustainability-oriented capabilities, redesign the business model around circular value creation, and assess whether environmental conditions facilitate or impede conversion into strategic advantage.

IX. LIMITATIONS AND FUTURE RESEARCH

The proposed empirical design has several limitations that should be acknowledged prospectively. Although the three-wave structure improves temporal separation, observational survey data support theory-consistent association and temporal ordering more strongly than definitive causal inference; longitudinal panel, archival, quasi-experimental, or mixed-method designs would

provide stronger evidence on capability development and business-model transformation. Multi-informant sampling reduces but does not eliminate key-informant and common-method bias. Construct operationalization remains especially important because AGC is less mature empirically than established dynamic-capability constructs, and the conceptual proximity of AGC, AI capability, sustainable AI capability, and SODC creates a nontrivial discriminant-validity challenge. Sectoral differences in AI intensity, regulatory exposure, and circularity opportunity may limit generalizability, making multigroup and industry-specific replication valuable. Finally, ET may plausibly operate as moderator, antecedent, nonlinear boundary condition, or configurational element; alternative specifications should therefore be compared rather than privileging a single interaction model by default.

X. CONCLUSION

This research develops an integrated strategic explanation of how responsibly governed AI may contribute to sustainable competitive advantage. The proposed sequence—AGC → SODC → CBMI → SCA—positions AI governance as an upstream organizational capability whose strategic value is realized through sustainability-oriented sensing, seizing, and reconfiguration and through the redesign of circular value creation, delivery, and capture. The demonstration in Section VII shows how the full empirical test can be reported and illustrates a pattern in which H1–H7 are supported, including a strengthening interaction under environmental turbulence.

REFERENCES

- [1] T. Birkstedt, M. Minkkinen, A. Tandon, and M. Mäntymäki, “AI governance: themes, knowledge gaps and future agendas,” *Internet Research*, vol. 33, no. 7, pp. 133–167, 2023. <https://doi.org/10.1108/INTR-01-2022-0042>
- [2] D. J. Teece, G. Pisano, and A. Shuen, “Dynamic capabilities and strategic management,” *Strategic Management Journal*, vol. 18, no. 7, pp. 509–533, 1997. [https://doi.org/10.1002/\(SICI\)1097-0266\(199708\)18:7<509::AID-SMJ882>3.0.CO;2-Z](https://doi.org/10.1002/(SICI)1097-0266(199708)18:7<509::AID-SMJ882>3.0.CO;2-Z)
- [3] D. J. Teece, “Explicating dynamic capabilities: the nature and microfoundations of (sustainable) enterprise performance,” *Strategic Management Journal*, vol. 28, no. 13, pp. 1319–1350, 2007. <https://doi.org/10.1002/smj.640>
- [4] S. L. Hart, “A natural-resource-based view of the firm,” *Academy of Management Review*, vol. 20, no. 4, pp. 986–1014, 1995. <https://doi.org/10.5465/amr.1995.9512280033>
- [5] T. Santa-Maria, W. J. V. Vermeulen, and R. J. Baumgartner, “How do incumbent firms innovate their business models for the circular economy? Identifying micro-foundations of dynamic capabilities,” *Business Strategy and the Environment*, vol. 31, no. 4, pp. 1308–1333, 2022. <https://doi.org/10.1002/bse.2956>
- [6] R. De Angelis, R. Morgan, and L. M. De Luca, “Open strategy and dynamic capabilities: A framework for circular economy business models research,” *Business Strategy and the Environment*, vol. 32, no. 7, pp. 4861–4873, 2023. <https://doi.org/10.1002/bse.3397>
- [7] D. Sjödin, V. Parida, and M. Kohtamäki, “Artificial intelligence enabling circular business model innovation in digital servitization: Conceptualizing dynamic capabilities, AI capacities, business models and effects,” *Technological Forecasting and Social Change*, vol. 197, pp. 122903, 2023. <https://doi.org/10.1016/j.techfore.2023.122903>
- [8] A. Madanaguli, D. Sjödin, V. Parida, and P. Mikalef, “Artificial intelligence capabilities for circular business models: Research synthesis and future agenda,” *Technological Forecasting and Social Change*, vol. 200, pp. 123189, 2024. <https://doi.org/10.1016/j.techfore.2023.123189>

- [9] L. Qiu, X. Jie, Y. Wang, and M. Zhao, "Green product innovation, green dynamic capability, and competitive advantage: Evidence from Chinese manufacturing enterprises," *Corporate Social Responsibility and Environmental Management*, vol. 27, no. 1, pp. 146–165, 2020. <https://doi.org/10.1002/csr.1780>
- [10] D. Witschel, D. Baumann, and K.-I. Voigt, "How manufacturing firms navigate through stormy waters of digitalization: the role of dynamic capabilities, organizational factors and environmental turbulence for business model innovation," *Journal of Management & Organization*, vol. 28, no. 3, pp. 681–714, 2022. <https://doi.org/10.1017/jmo.2022.44>
- [11] E. Papagiannidis, P. Mikalef, and K. Conboy, "Responsible artificial intelligence governance: A review and research framework," *Journal of Strategic Information Systems*, vol. 34, no. 2, pp. 101885, 2025. <https://doi.org/10.1016/j.jsis.2024.101885>
- [12] P. Mikalef and M. Gupta, "Artificial intelligence capability: Conceptualization, measurement calibration, and empirical study on its impact on organizational creativity and firm performance," *Information & Management*, vol. 58, no. 3, pp. 103434, 2021. <https://doi.org/10.1016/j.im.2021.103434>
- [13] S. A. Qalati and F. Siddiqui, "Organizational sustainable artificial intelligence capabilities scale development, validation, and implications," *Journal of Innovation & Knowledge*, vol. 11, pp. 100863, 2026. <https://doi.org/10.1016/j.jik.2025.100863>
- [14] L. B. L. Amui, C. J. C. Jabbour, A. B. L. de Sousa Jabbour, and D. Kannan, "Sustainability as a dynamic organizational capability: a systematic review and a future agenda toward a sustainable transition," *Journal of Cleaner Production*, vol. 142, pp. 308–322, 2017. <https://doi.org/10.1016/j.jclepro.2016.07.103>
- [15] K. V. Bhadra, T. J. Kamalanabhan, and S. K. Singh, "Evolution of dynamic capabilities for business sustainability performance: Evidence from the Indian manufacturing sector," *Business Strategy and the Environment*, 2024. <https://doi.org/10.1002/bse.3767>
- [16] N. Bari, R. Chimhundu, and K. C. Chan, "Interrelation between Sustainable Dynamic Capabilities, Corporate Sustainability, and Sustained Competitive Advantage," *Sustainability*, vol. 16, no. 7, pp. 2864, 2024. <https://doi.org/10.3390/su16072864>
- [17] M. Geissdoerfer, M. P. P. Pieroni, D. C. A. Pigosso, and K. Soufani, "Circular business models: A review," *Journal of Cleaner Production*, vol. 277, pp. 123741, 2020. <https://doi.org/10.1016/j.jclepro.2020.123741>
- [18] M. P. P. Pieroni, T. C. McAloone, and D. C. A. Pigosso, "Business model innovation for circular economy and sustainability: A review of approaches," *Journal of Cleaner Production*, 2019. <https://doi.org/10.1016/j.jclepro.2019.01.036>
- [19] P. Centobelli, R. Cerchione, D. Chiaroni, P. Del Vecchio, and A. Urbinati, "Designing business models in circular economy: A systematic literature review and research agenda," *Business Strategy and the Environment*, 2020. <https://doi.org/10.1002/bse.2466>
- [20] M. Geissdoerfer, D. Vladimirova, and S. Evans, "Sustainable business model innovation: A review," *Journal of Cleaner Production*, vol. 198, pp. 401–416, 2018. <https://doi.org/10.1016/j.jclepro.2018.06.240>
- [21] T. van Eechoud and A. Ganzaroli, "Exploring the role of dynamic capabilities in digital circular business model innovation: Results from a grounded systematic inductive analysis of 7 case studies," *Journal of Cleaner Production*, vol. 401, pp. 136665, 2023. <https://doi.org/10.1016/j.jclepro.2023.136665>
- [22] J. Block, T. Clauss, H. Speth, et al., "Dynamic Capabilities as Drivers of Circular Business Models: Exploring Direct and Indirect Relationships," *Journal of Product Innovation Management*, 2026. <https://doi.org/10.1111/jpim.70033>
- [23] J. Wang, S. Chaudhary, M. M. Kamal, S. S. Almasabi, and S. Remsei, "AI-Enabled Circular Business Model Transition for Mitigating Climate Change: A Natural Resource-Based View Perspective on Business Strategies," *Business Strategy and the Environment*, 2026. <https://doi.org/10.1002/bse.70649>
- [24] R. Adams, S. Jeanrenaud, J. Bessant, D. Denyer, and P. Overy, "Sustainability-oriented Innovation: A Systematic Review," *International*

- Journal of Management Reviews, vol. 18, no. 2, pp. 180–205, 2016. <https://doi.org/10.1111/ijmr.12068>
- [25] X. Xu and A. G. Sam, “Environmental Sustainability and Business Profitability: Profiling Winners and Losers With Machine Learning,” *Business Strategy and the Environment*, vol. 34, pp. 5205–5239, 2025. <https://doi.org/10.1002/bse.4236>
- [26] M. H. Al Dhaheri, S. Z. Ahmad, and A. Papastathopoulos, “Do environmental turbulence, dynamic capabilities, and artificial intelligence force SMEs to be innovative?” *Journal of Innovation & Knowledge*, vol. 9, no. 3, pp. 100528, 2024. <https://doi.org/10.1016/j.jik.2024.100528>
- [27] L. Turulja and N. Bajgoric, “Innovation, firms’ performance and environmental turbulence: is there a moderator or mediator?” *European Journal of Innovation Management*, vol. 22, no. 1, pp. 213–232, 2019. <https://doi.org/10.1108/EJIM-03-2018-0064>
- [28] J. Henseler, C. M. Ringle, and M. Sarstedt, “A new criterion for assessing discriminant validity in variance-based structural equation modeling,” *Journal of the Academy of Marketing Science*, vol. 43, pp. 115–135, 2015. <https://doi.org/10.1007/s11747-014-0403-8>
- [29] P. M. Podsakoff, S. B. MacKenzie, J.-Y. Lee, and N. P. Podsakoff, “Common method biases in behavioral research: A critical review of the literature and recommended remedies,” *Journal of Applied Psychology*, vol. 88, no. 5, pp. 879–903, 2003. <https://doi.org/10.1037/0021-9010.88.5.879>

APPENDIX A. C-SUITE EXECUTIVE PRIMARY-DATA INSTRUMENT

Purpose: To measure how AI governance capability, sustainability-oriented dynamic capabilities, circular business model innovation, and environmental turbulence relate to sustainable competitive advantage at the organizational level. Intended respondents are C-suite or equivalent executives with direct knowledge of enterprise strategy, sustainability, AI/digital transformation, operations, innovation, or governance. Unless otherwise stated, rate each statement from 1 (strongly disagree) to 7 (strongly agree).

A. Eligibility and Organization Profile

Code	Question	Response format
S1	Current executive role	CEO / CSO-Sustainability / Chief Strategy Officer / COO / CIO-CDO-CTO / Other executive-committee role
S2	Strategic knowledge	I have direct organization-wide knowledge of the organization’s sustainability strategy.
S3	AI knowledge	I have direct knowledge of how AI or AI-enabled analytics are used in significant organizational decisions or processes.
S4	Tenure in current organization	Less than 1 year / 1–2 / 3–5 / 6–10 / More than 10 years
S5	Organization size	50–249 / 250–999 / 1,000–4,999 / 5,000–9,999 / 10,000+ employees
S6	Primary industry	Manufacturing / Financial services / Technology / Energy & utilities / Consumer & retail / Healthcare / Logistics & transport / Professional services / Other
S7	Geographic scope	Domestic / Regional / Multinational /

		Global
S8	AI maturity	Exploratory / Limited deployment / Multiple functional deployments / Enterprise-scale / AI embedded in strategic decision systems
S9	Sustainability integration	Peripheral/compliance-led / Functional initiatives / Cross-functional / Embedded in corporate strategy / Embedded in strategy and capital allocation

B. Wave 1 — AI Governance Capability (AGC)

Item	Executive statement (1 = strongly disagree; 7 = strongly agree)
AGC1	Our organization has clearly assigned executive decision rights for material AI use.
AGC2	Accountability for AI-related outcomes and risks is explicit at senior leadership level.
AGC3	AI-relevant data quality, access, provenance, and stewardship are governed through formal enterprise processes.
AGC4	Material AI applications are subject to systematic risk, ethics, and compliance oversight before and after deployment.
AGC5	Senior leaders require appropriate transparency or explainability for consequential AI-supported decisions.
AGC6	Stakeholder and societal consequences are considered when governing significant AI applications.
AGC7	AI governance priorities are explicitly aligned with the organization's sustainability and long-term strategic objectives.

C. Wave 2 — Sustainability-Oriented Dynamic Capabilities (SODC)

Item	Executive statement (1 = strongly disagree; 7 = strongly agree)
SODC1	We systematically identify sustainability-related changes that could alter our competitive position.
SODC2	We use external and internal intelligence to detect emerging environmental, social, regulatory, and resource-related opportunities.
SODC3	When sustainability opportunities are identified, senior management can commit resources quickly enough to act on them.
SODC4	Sustainability priorities are translated into coordinated initiatives across functions rather than remaining within a specialist team.
SODC5	We reconfigure processes, assets, technologies, and capabilities when sustainability objectives require

	strategic change.
SODC6	We redesign partnerships and ecosystem relationships when new sustainability opportunities cannot be captured internally.
SODC7	Our organization learns from sustainability initiatives and incorporates that learning into future strategic decisions.

D. Wave 2 — Environmental Turbulence (ET)

Item	Executive statement (1 = strongly disagree; 7 = strongly agree)
ET1	Technologies relevant to our business and sustainability agenda change rapidly.
ET2	Customer and market expectations concerning sustainability change unpredictably.
ET3	Regulatory and policy requirements affecting sustainability or AI change substantially over time.
ET4	Competitive actions in digitalization, sustainability, or circularity are difficult to anticipate.
ET5	Strategic assumptions in our industry become obsolete faster than they did in the past.

E. Wave 3 — Circular Business Model Innovation (CBMI)

Item	Executive statement (1 = strongly disagree; 7 = strongly agree)
CBMI1	We have redesigned elements of our value proposition to reduce resource use, waste, or lifecycle impacts.
CBMI2	We increasingly design products, services, or processes for reuse, repair, recovery, remanufacture, recycling, or extended life.
CBMI3	We have changed how value is created and delivered in order to retain resources or materials within productive use for longer.
CBMI4	We use digital or AI-enabled information to improve lifecycle visibility, resource-loop decisions, or circular operations.
CBMI5	We collaborate with suppliers, customers, or ecosystem partners to enable circular value flows that could not be achieved by our organization alone.
CBMI6	We have adapted revenue, pricing, ownership, service, or value-capture mechanisms to support circular or lifecycle-based models.
CBMI7	Circularity considerations influence major business-model and investment decisions rather than remaining isolated operational initiatives.

F. Wave 3 — Sustainable Competitive Advantage (SCA)

Item	Executive statement (1 = strongly disagree; 7 = strongly agree)
SCA1	Our sustainability-related capabilities provide differentiation that competitors would find difficult to reproduce quickly.
SCA2	Sustainability and circularity strengthen our organization's long-term strategic resilience.
SCA3	Our sustainability approach improves our ability to create new strategic options, innovations, or growth opportunities.
SCA4	Our sustainability performance strengthens stakeholder trust and legitimacy in ways that support competitive position.
SCA5	We are better positioned than key competitors to respond to sustainability-related market, regulatory, or resource shifts.
SCA6	The integration of sustainability into strategy contributes to durable long-term value creation, not only short-term compliance outcomes.

G. Executive Control Variables and Validation Items

Code	Variable	Response
C1	Strategic sustainability maturity	Five-level maturity scale from compliance-led to fully embedded in corporate strategy and capital allocation
C2	AI governance maturity	Five-level maturity scale from informal/no governance to board/executive-integrated governance
C3	Circularity maturity	Five-level maturity scale from isolated efficiency projects to enterprise/ecosystem circular business model
C4	Board oversight	Does the board or a board committee formally oversee sustainability and/or material AI risks? Yes / No / Partly
C5	External assurance	Are material sustainability metrics externally assured? Yes / No / Selected metrics only
C6	Objective corroboration	Optional entry of publicly disclosed sustainability target, circularity KPI, or annual-report reference for validation
AC	Attention check	For data-quality purposes, please select "Agree" for this item.